Addressing uncertainty in efficient mitigation of agricultural greenhouse gas emissions

Eory, V; Topp, CFE; Butler, A; Moran, D

Published in:
Journal of Agricultural Economics

DOI:
10.1111/1477-9552.12269

First published: 30/04/2018

Addressing uncertainty in efficient mitigation of agricultural greenhouse gas emissions

Vera Eory, Cairistiona F. E. Topp, Adam Butler and Dominic Moran[1]

[Original submitted March 2017, Revision received September 2017, Accepted October 2017]

Abstract

The agricultural sector, as an important source of greenhouse gas (GHG) emissions, is under pressure to reduce its contribution to climate change. Decisions on financing and regulating agricultural GHG mitigation are often informed by cost-effectiveness analysis of the potential GHG reduction in the sector. A commonly used tool for such analysis is the bottom-up marginal abatement cost curve (MACC) which assesses mitigation options and calculates their cumulative cost-effective mitigation potential. MACCs are largely deterministic, typically not reflecting uncertainties in underlying input variables. We analyse the uncertainty of GHG mitigation estimates in a bottom-up MACC for agriculture, for those uncertainties capable of quantitative assessment. Our analysis identifies the sources and types of uncertainties in the cost-effectiveness analysis and estimates the statistical uncertainty of the results by propagating uncertainty through the MACC via Monte Carlo analysis. For the case of Scottish agriculture, the uncertainty of the cost-effective abatement potential from agricultural land, as expressed by the coefficient of variation, was between 9.6% and 107.3% across scenarios. This means that the probability of the actual abatement being less than half of the estimated abatement ranged from <1% (in the scenario with lowest uncertainty) to 32% (in the scenario with highest uncertainty). The main contributors to uncertainty are the adoption rate and abatement rate. While most mitigation options appear to be 'win-win' under some scenarios, many have a high probability of switching between being cost-ineffective and cost-effective.

Keywords: Agriculture, greenhouse gas mitigation, marginal abatement costs curve, uncertainty

JEL Classifications: Q15, Q18, Q52

---

[1] Vera Eory (contact: vera.eory@sruc.ac.uk), Cairistiona Topp and Dominic Moran are all in the Research Division, SRUC, Edinburgh, UK. Adam Butler is with Biomathematics & Statistics Scotland, Edinburgh, UK. This paper was funded by the Rural & Environment Science & Analytical Services Division of the Scottish Government.

.

1. Introduction

Policies to promote climate change mitigation should be informed by scientific evidence on the effectiveness of alternative greenhouse gas (GHG) mitigation options, i.e. their GHG abatement potential, cost and their on-farm adoption rates. This information will be subject to uncertainty, which if ignored, can result in inefficient policy. Robust policies, which aim to achieve their environmental, economic and social objectives across a range possible futures, need to take these uncertainties into account (Kunreuther *et al.*, 2014; Lempert and Schlesinger, 2000).

Uncertainty analysis has become integral in key areas of climate science and its policy interface. This includes the physical sciences (e.g. climate modelling), and models attempting to understand the economy-wide effects of climate change (Peterson, 2006). Golub *et al.* (2014) described uncertainty approaches used in integrated assessment models. Such approaches are particularly valuable for top-down (global, regional) policy scenarios, but limited for advising policy at the national level where information on specific mitigation options and sub-sectors is required.

This paper considers mitigation uncertainties in agriculture, a sector that is implicated as a significant source of GHG emissions both nationally and globally; agriculture (not including land use change and forestry) has been estimated to account for approximately 14% of global anthropogenic emissions in 2010 (IPCC, 2014) and 17% of anthropogenic emissions in Scotland (Salisbury *et al*., 2015). To date, uncertainty regarding the agricultural sector has been considered in the context of inventory of sources that identify total emissions (Milne et al., 2014). However, there has been less focus on how uncertainties influence mitigation policy that is informed by a systematic analysis of sector-specific mitigation options and their cost-effectiveness. Such analysis is challenging due to the spatial variation in agricultural GHG emissions that constrains robust GHG emission and mitigation quantification (Olander *et al*., 2013). These difficulties hinder the development of GHG mitigation policies in agriculture. For example market-based instruments such as taxes or trading require robust emissions monitoring, while voluntary and regulatory instruments would also benefit from information on the uncertainties to prioritise support for mitigation options. Therefore, information on uncertainty associated with the cost-effectiveness of mitigation should be an integral part of the scientific evidence base supporting the agricultural GHG mitigation agenda.

Most research on the economics of GHG mitigation in agriculture has largely ignored how uncertainties influence cost-effectiveness. Emerging information on emission uncertainty has been represented in some farm-level GHG modelling (Gibbons *et al*., 2006; Zehetmeier *et al*., 2014) and in work focussing on specific mitigation options such as biogas electricity generation (Meyer-Aurich *et* *al*., 2012) and low nitrogen livestock feeding options (Pierer *et al*., 2016). Uncertainty assessment is also possible with agent-based modelling of mitigation options, as described in Berger and Troost (2014). However, the complexity of incorporating uncertainty in the analysis often hinders knowledge exchange between scientist and policy makers, and can result in a limited integration of uncertainty information in the decision making process (Knaggard, 2013). Mutual engagement from both scientists and policy makers is required to overcome some of the obstacles in communicating and utilising uncertainty information (Milne *et al.*, 2015; Smith and Stern, 2011). To this end, policy support tools such as marginal abatement cost curves (MACC) need to be augmented with a transparent uncertainty analysis.

MACCs are decision making tools used to estimate the optimal level of mitigation effort and to prioritise mitigation options in terms of their cost-effectiveness (i.e. the cost of GHG abatement, e.g. £ t CO_2e^{-1}). MACCs show the cost of reducing pollution by one additional unit as a function of the cumulative pollution reduction, featuring mitigation actions in the order of their cost-effectiveness. The cost-effective mitigation potential is estimated as the mitigation potential under a notional carbon price threshold (which, in turn, represents the marginal damage cost). MACCs have informed climate change policy globally (Kesicki and Strachan, 2011), enabling information on the cost-effectiveness of mitigation to be conveyed in a relatively simple way. While the visual attractiveness of MACCs can facilitate access to rather complex information, they can potentially disguise information on key assumptions, especially the key uncertainties. The absence of an uncertainty analysis in MACCs has been identified as a potential methodological shortcoming (Kesicki and Ekins, 2012), perhaps especially for the agricultural and land use sector. High uncertainty in cost-effective abatement reduces the chances that chosen policies will meet mitigation targets, which increases the overall mitigation costs.

We provide a systematic account of uncertainty in the context of cost-effectiveness of GHG mitigation in agriculture, quantifying mitigation uncertainty and highlighting the most important underlying factors. We use existing MACC data to estimate the uncertainty of the cost-effective total abatement potential and the cost-effectiveness and abatement of individual mitigation options for UK agriculture (Moran *et al*., 2011). By doing so, we demonstrate a solution for a shortcoming which affects numerous agricultural MACCs around the world (Eory *et al.*, 2017) and hinders agri-environmental decision making.

The paper is structured as follows. The sources and types of uncertainties in agricultural GHG mitigation assessment and MACCs are explored in Section 2. The methodology is explained in Section 3, with the results presented and discussed in Section 4. Conclusions are drawn in Section 5.

2. Uncertainty in economic assessment of agricultural GHG mitigation

Uncertainties associated with GHG mitigation options are embedded in a complex feedback loop linking the environment and the economy. Figure 1 highlights the interactions between the economy and the climate, illustrating some of the sources of uncertainty. Environmental processes (GHG concentrations and mitigation, weather, systems impact) are dominated by biogeochemical uncertainties, while the societal processes (effects on individual behaviour, economic activities, policy) are associated with additional uncertainties related to technology choice, economic processes, politics, human behaviour and value uncertainty (heterogeneity of personal values).

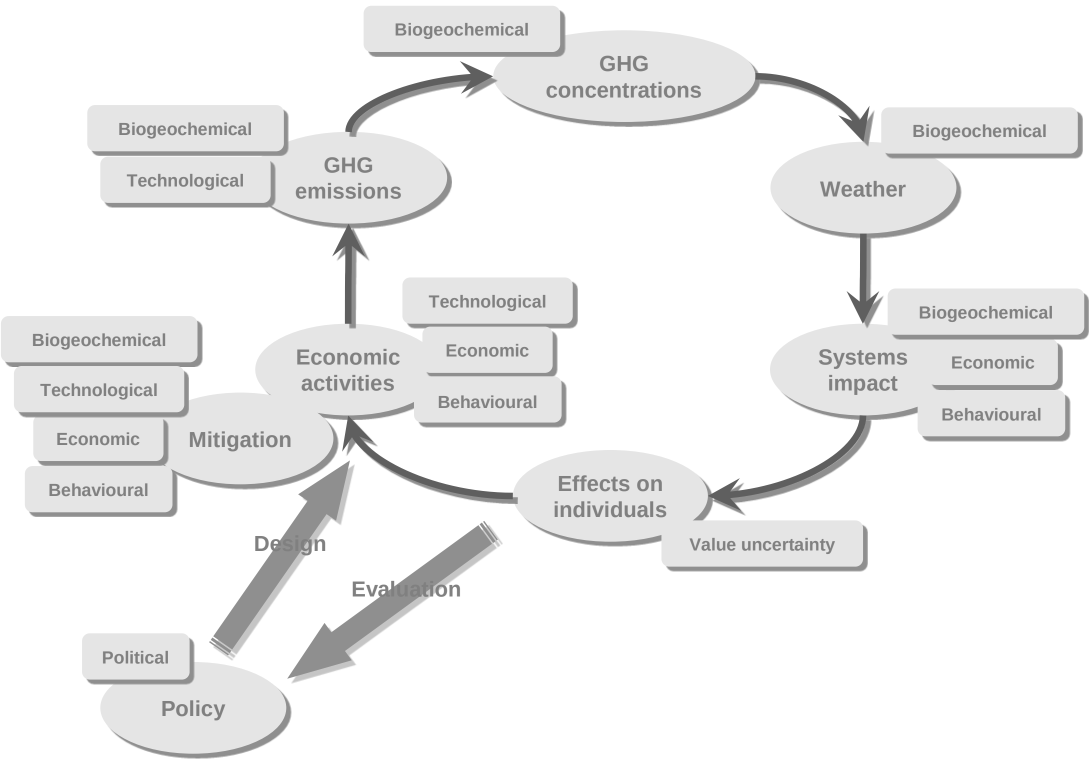

Figure 1 Sources of uncertainty (in squares) in the climate change feedback loop (adapted from Smith and Stern, 2011)

In agriculture and land use, biogeochemical processes have a significant influence on land use activities and associated emissions, playing a key role in determining the effectiveness of mitigation options. Hence models of land use decisions (e.g. cropping activities, livestock densities, farm management activities) are highly affected by biogeochemical uncertainties. For example, the uncertainty in the predictions of future weather conditions generates uncertainty in nitrous oxide (N_2O)

emission estimates, resulting in uncertainty in its estimated mitigation. Weather conditions also affect farmer decision-making, e.g. the amount and timing of nitrogen (N) fertiliser application, affecting N_2O emissions and ultimately the effectiveness of mitigation options. The economic and policy environments influence land use decisions and associated agricultural management activities. Therefore, related uncertainties also intervene in model representations. For example, those related to changes in market prices, coupled with agricultural and energy policies, will affect both the uncertainty in land use and the uncertainty of financial costs and benefits of GHG mitigation options. A further uncertainty is related to farmer and land manager behaviours, which, combined with the policy environment, determine the diffusion of mitigation technologies with a direct effect on total GHG abatement.

Only some of these uncertainties can be quantified. Quantifiable uncertainties are referred to as statistical uncertainty (also referred to as imprecision, Knightian risk, or conditional probability in other studies). These can be expressed via probabilities and can be included in numeric models. For example, the 100-year global warming potential of N_2O is estimated to be in the range of 209-387 with 90% confidence and a mean estimate of 298 (IPCC, 2013). Agricultural data on current and historic cropping and livestock activities, input and output prices, experimental data of gaseous emissions and carbon sequestration all have statistical uncertainties associated with them (though not necessarily quantified). Beyond uncertainties in observational and experimental data, statistical uncertainty also arises from any model outputs used. These can be quantified if a direct comparison of model outcomes with observed data (i.e. validation) is possible. For example, results from farm economic modelling predicting profit levels can be compared with existing time series data, allowing quantification of model errors.

Some uncertainties cannot be quantified statistically. So-called deep uncertainty (or ambiguity, Knightian uncertainty) can arise for many reasons, and is particularly relevant to models of complex systems that predict future outcomes (Hallegatte *et al.*, 2012; Smith and Stern, 2011), for example how agricultural production may be influenced by future extreme weather events. A third type of uncertainty (value uncertainty) occurs when values depend on personal judgement. Examples include discount rates, or the value of human life (Kann and Weyant, 2000). Value uncertainty can be illustrated using scenarios to represent the different choice of values. As probabilities cannot be assigned to the different values, the results of the scenarios cannot be aggregated in the statistical sense.

3. Methodology

Our analysis consists of two parts: i) establishing an inventory of the uncertainties that influence the cost-effectiveness of agricultural GHG mitigation; ii) quantitative appraisal of uncertainty associated with the cost-effective GHG mitigation. This section provides an overview of the MACC model, the methodology for the qualitative assessment and the uncertainty propagation.

The MACC model

A bottom-up MACC represents the annual net costs and annual GHG abatement potential of the mitigation options and derives the annual cost-effectiveness of the options as the ratio of these. Uncertainties in the abatement potential and cost of the mitigation options and uncertainty in the marginal damage cost curve (i.e. the carbon price) in turn result in uncertainty in the economic optimum (Figure 2).

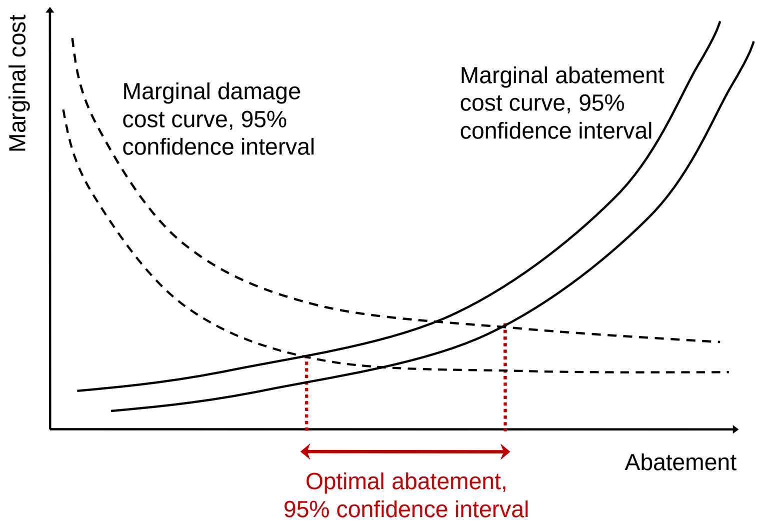

Figure 2 Effect of uncertainty on the optimal abatement level (adapted from Smith and Stern, 2011)

Our quantitative analysis is based on the UK agricultural GHG MACC (Moran *et al.* (2011)), which provides a description of the MACC methodology and the mitigation options originally reviewed in Moran *et al.* (2008). Input data on abatement rates and applicability have been updated to reflect environmental conditions and farming practices in Scotland. A brief description of the MACC calculations, the main input data and the mitigation options are presented in the on-line Supplementary Material.

In the UK study, annual abatement was calculated for the years 2012, 2017 and 2022, considering interactions between the options, i.e. possible synergies and trade-offs in mitigation if more than one mitigation option is implemented at the same time on the same farm. Four adoption scenarios reflected different assumptions about the future policy environment: low, central, high and maximum adoption, assuming adoption levels of 7-18%, 45%, 85-92% and 100% respectively. The mitigation options were assessed both in terms of their cost-effectiveness as in the MACC (i.e. considering interactions between them - ‘interaction cost-effectiveness’) and as if implemented as a single option (‘stand-alone cost-effectiveness’).

Our present study focuses on the crop and soil management mitigation options of the UK study, namely: using biological fixation to provide N inputs (BiolFix); reducing nitrogen fertiliser (NRed); improving land drainage (Drain); avoiding nitrogen application in excess (NExcessRed); using manure nitrogen to its full extent (NOrgFull); introducing of new species (including legumes) (NewSp); improving the timing of mineral nitrogen application (MinNTime); using controlled release fertilisers (CRF); using nitrification inhibitors (NI); improving the timing of slurry and poultry manure application (OrgNTime); adopting systems less reliant on inputs (LowInput); adopting plant varieties with improved N-use efficiency (HighNUE); separating slurry applications from fertiliser applications by several days (SepSlFert); using reduced tillage and no-tillage techniques (RedTill); using composts and straw-based manures in preference to slurry (Compost).

Uncertainty assessment

For the qualitative analysis, the main drivers of the uncertainties in each group of MACC inputs were explored, and the framework for the sources and types of uncertainties (Section 2) was used to map the sources of uncertainty (e.g. biogeochemical, economic) and the type of uncertainties (e.g. statistical, deep).

The quantitative analysis estimated the statistical uncertainty of the MACC. Statistical uncertainty is commonly represented by a probability density function (PDF), describing its shape (i.e. distribution), mode (the value associated with the highest probability) and width (e.g. 95% confidence interval). As information on the statistical uncertainty of the input variables is scarce, the shape of the PDFs were defined to follow theoretical distributions, the input values of the variables in the original study (Moran *et al.*, 2008) were used as the mode and the width of the PDFs were based on the authors' judgment. The inputs of the MACC model were originally derived from agricultural statistics, experimental data, biophysical and economic models, and, in the lack of these, expert opinion. Table 1 provides a description of these inputs, grouped into seven categories. To examine the effect of the distribution and confidence interval of the PDFs, nine PDFs were defined for each input variable: a combination of three different distributions and three different confidence intervals.

Each of the three distributions (triangular, censored normal and truncated normal) allows the boundaries of the parameter space to be dealt with in a particular way, i.e. the fact that some input variables must lie between 0 and 1. Table 1 shows the parameter space of each input group. For the triangular distribution, probability is a linear function of distance from the mode. For the censored normal and truncated normal distribution it is assumed that the distribution of probabilities can be represented by a normal distribution bounded by the parameter space of the input variable. These two distributions differ solely in whether there is a non-zero probability of obtaining values that lie exactly at the boundaries of the parameter space; the censored normal allows this, the truncated normal does not. The two distributions are equivalent to each other and equivalent to a conventional normal distribution for those input variables that have no boundaries on their parameter space (net cost, and, for some mitigation options, abatement rate).

Table 1 Characteristics of the three levels of uncertainty assigned to the input variables of the MACC model

Input group	Description and unit	Parameter space	Confidence interval[a]		
			Wide PDF	Medium PDF	Narrow PDF
N_2O GWP	100 year GWP [kg CO_2e (kg N_2O)$^{-1}$]	(0, ∞)	Mode * 0.6	Mode * 0.4	Mode * 0.2
Activity levels	Areas of land under different type of crops [ha]	(0, ∞)	Mode * 0.6	Mode * 0.4	Mode * 0.2
Applicability	Proportion of land area where an option can be feasibly applied [-]	(0, 1)	1.0	0.6	0.2
Adoption	Level of implementation of an option by farmers across Scotland, on land areas where the option is applicable [-]	(0, 1)	1.0	0.6	0.2
Interaction factors	Factor assigned to each possible pairs of options, describing the synergies and trade-offs in the GHG effectiveness of the options [-]	(0, ∞)	1.0	0.6	0.2
Abatement rate	Technical GHG effectiveness of the options [t CO_2e ha^{-1} year^{-1}]	(0, ∞) (-∞, ∞)	Mode * 4	Mode * 2	Mode
Net annual cost	Difference between the gross margin of the farm with and without the option applied, calculated with a profit maximising farm model [£ ha^{-1} year^{-1}]	(-∞, ∞)	Mode * 4	Mode * 2	Mode

[a] confidence interval is 95% for the censored normal and the truncated normal distribution, 100% for the triangular distribution

The confidence interval was defined to include 95% of probability, or 100% for the triangular distribution. To reflect the lack of robust information on the uncertainties, three levels of uncertainty were assigned for each input variable: high, medium or low, represented by a wider, a medium and a narrower confidence interval, respectively, and the corresponding PDFs are labelled as “wide”, “medium” and “narrow” PDF. The confidence interval of those input variables for which parameter space was not bounded (e.g. net cost) were defined as a multiples of the mode, whilst if the parameter space was bounded (e.g. adoption) the confidence interval was defined in absolute terms.

The widths of the confidence intervals were based on the authors’ judgment. Activity levels and the global warming potential of N_2O were assumed to have the lowest uncertainty; the former based on the fact that annual farming statistics in Scotland are estimated with relatively high certainty, the latter based on the confidence range of N_2O GWP reported by the International Panel of Climate Change (IPCC), which is ±30% (Myhre *et al*., 2013).

Applicability, adoption and interaction factor (IF) values were based on expert judgement in the original MACC exercise, therefore greater levels of uncertainty were assigned to these than to GWP and activity levels. Applicability and adoption can be of any value between 0 and 1, where 1 represents applicability on 100% of agricultural land, and 100% adoption, respectively. Most of the IFs fall between 0 and 1. The IF values that represent synergies, for example the interaction effect between ‘improving land drainage’ and ‘using nitrification inhibitors’, have values above 1, meaning that one option enhances the mitigation effect of the other. The uncertainties of applicability, adoption and interaction factors are assumed not to be proportional to their value and were expressed in absolute terms. Net costs of mitigation options were assigned relatively high levels of uncertainty. These were derived from a farm level financial model with no information on their uncertainty. Abatement rates were also based on expert judgement and were similarly assigned high levels of uncertainty. The abatement rates of seven of the 15 mitigation options were assumed to be non-negative. The remaining eight options were assumed to have some probability for negative values, that is, to increase, rather than decrease, GHG emissions (see on-line Supplementary Material).

Statistical uncertainty of the input variables was propagated through the MACC model via Monte Carlo analysis run for all 3 x 4 x 3 x 3 x 8 = 864 combinations of year (2012, 2017, 2022), adoption scenario (LFP, CFP, HFP and MTP), level of uncertainty (narrow PDF, medium PDF, wide PDF), PDF shape (censored normal, truncated normal, triangular) and input group. For each of the seven input groups, the input uncertainties were propagated separately while the other inputs were maintained at their mean value. In the final set of Monte Carlo run all the uncertainties were propagated jointly through the model.

The Monte Carlo analysis for each combination involved simulating 2,500 sets of input variable values using the relevant PDFs, and then using each set of simulated input variables for calculation of the MACC to generate a PDF for the MACC outputs. The key outputs collected were

i) the distribution of the cost-effectiveness and abatement potential of each mitigation option;
ii) the distribution of the cost-effective abatement potential. This corresponds to the aggregated annual abatement potential of all of the options with a cost-effectiveness value below the shadow price of carbon (SPC) (£29 (CO_2e t)$^{-1}$ as estimated by Price *et al.* (2007)).

Lacking any quantitative information on possible dependence between the different groups of inputs of uncertainty, it is assumed that the uncertainties associated with the different groups of inputs are independent for the simulations that combine all seven groups.

4. Results and discussion

Qualitative uncertainty assessment

The main drivers, sources and types of uncertainties affecting each input group are presented in Table 2. Economic and biogeochemical uncertainty affects all but two input groups. Economic uncertainty is not prominent in abatement rate and interactions, and biogeochemical uncertainty is not important for the adoption levels and costs of the options. Uncertainty in farmer behaviour is important to the abatement potential, the adoption of the options, and the interactions between them. Uncertainty regarding farming technologies affects the abatement rate, interactions and the costs of the options. Finally, agri-environmental policy uncertainty mainly impacts the activity levels, adoption rates and costs.

Multiple statistical uncertainties characterise all of the MACC inputs. These arise from the use of sample observational data, experimental data (due to the accuracy and random error of the measurements), and modelled data (uncertainty in the data use and modelling uncertainty) in the MACC calculations. These uncertainties can in theory be quantified. But this information is not always reported in a form suitable for subsequent economic assessments. For some inputs (e.g. abatement and adoption rates) MACCs often rely on expert knowledge, where quantification of uncertainties is even more difficult and typically ignored.

Deep uncertainties characterise complex and/or future values that can only be modelled but not measured. Since MACCs are used as *ex-ante* tools, deep uncertainties are inherent in all of the inputs as a result of modelling the future of a complex ecological-economic system.

Value uncertainties exist regarding the global warming potential (GWP) metric and the discount rate, both depending on the policy goal and the time horizon considered, and both potentially leading to contrasting MACC scenarios.

Table 2 Inventory of uncertainties in the economic assessment of agricultural GHG mitigation

Input group	Driver of uncertainty	Source of uncertainty	Type of uncertainty
Global warming potential (GWP) of GHGs	Variability in the atmospheric processes	Biogeochemical	Statistical
	Future atmospheric processes	Biogeochemical	Statistical and deep
	Choice of GWP metric	Economic	Value
Agricultural activity levels (e.g. 0.9 M ha permanent grassland)	Future changes in farming activities as they depend on changes in climate and soil characteristics	Biogeochemical	Statistical and deep
	Current agricultural activity, prices and other economic variables	Economic	Statistical
	Future changes in farming activities as they depend on demographic and economic changes	Economic and political	Statistical and deep
GHG abatement rate of the mitigation options (e.g. 0.1 t CO_2e/ha/year) AND Biophysical interactions between the mitigation options (e.g. 10% reduction in the GHG abatement of option A if applied together with option B)	Variability of the weather and in the soil processes involved in N_2O emissions	Biogeochemical	Statistical and deep
	Future soil processes as they depend on changes in climate and soil characteristics	Biogeochemical	Statistical and deep
	Ways farmers will implement the mitigation options in practice	Behavioural	Statistical and deep
	Future changes in the abatement efficacy of the mitigation options	Technological	Statistical and deep
Applicability of the mitigation options (e.g. % of land area)	Variability in weather and soil types	Biogeochemical	Statistical
	Types of current and future farming systems	Economic	Statistical and deep
Likely additional adoption of the mitigation options by farmers (e.g. 45% of land area)	Current farm management practices	Economic	Statistical
	Variability in farmers' behaviour	Behavioural	Statistical
	Farmers' future behaviour	Behavioural	Statistical and deep
	Future changes in the economy and farming	Economic and political	Statistical and deep
Annualised net cost of the mitigation options (e.g. £1.40 /ha/year)	Current prices, costs, farm finances	Economic	Statistical
	Future changes farming practices	Technological	Statistical and deep
	Future prices, costs, farm finances	Economic and political	Statistical and deep
	Choice of discount rate	Economic	Value

Quantitative uncertainty assessment

Uncertainty of the cost-effective GHG abatement

For the year 2022, CFP, truncated normal distribution, medium PDF and all input group uncertainties combined, the mean cost-effective GHG abatement is 875 kt CO_2e, the standard deviation is 277 kt CO_2e. The coefficient of variation (CV), which is a relative metric (the ratio of the standard deviation to the mean), is 32%. In other words, the true value of the cost-effective GHG abatement lies between 336 and 1,415 kt CO_2e with 95% certainty (the 95% confidence interval is 1.96 times the standard deviation for normal distributions). Moran *et al.* (2008) estimated the same mitigation options to provide 805 kt CO_2e in 2022 under the SPC in Scotland; the difference being due both to some differences in the input values and also to the difference in the method regarding interaction calculations (in Moran *et al.* (2008) the interaction calculation was considering the whole UK while in this paper only Scotland was included in the interaction calculations).

Comment [DH1]: I am not sure how I should interpret, or even understand this comparison?

The uncertainties of the cost-effective abatement for the truncated normal distribution are presented in Figure 3. The uncertainty in absolute terms increases with increasing mean cost-effective abatement, but the relative uncertainty is higher with lower abatement. The distributions become skewed in the higher uncertainty scenarios, as can be seen from the increasing distance between the median and the mean values.

When propagating the uncertainties of all the input variables across all combinations of year, adoption scenario, level of uncertainty and PDF shape, the CV was between 9.6% and 107.3%, with an average of 38.3%. The lowest of these values (9.6% CV) was associated with the scenario MTP, 2022, narrow PDFs, triangular distribution, and the highest uncertainty (107.3% CV) was found for the LFP, 2012, wide PDFs, censored normal distribution. The input variables' uncertainties contribute to the uncertainty of the cost-effective abatement at a varying level: the adoption and abatement rates were the most important contributors and the uncertainties of the net cost and activity level were the least important in the output uncertainty (see further details in the Supplementary Material).

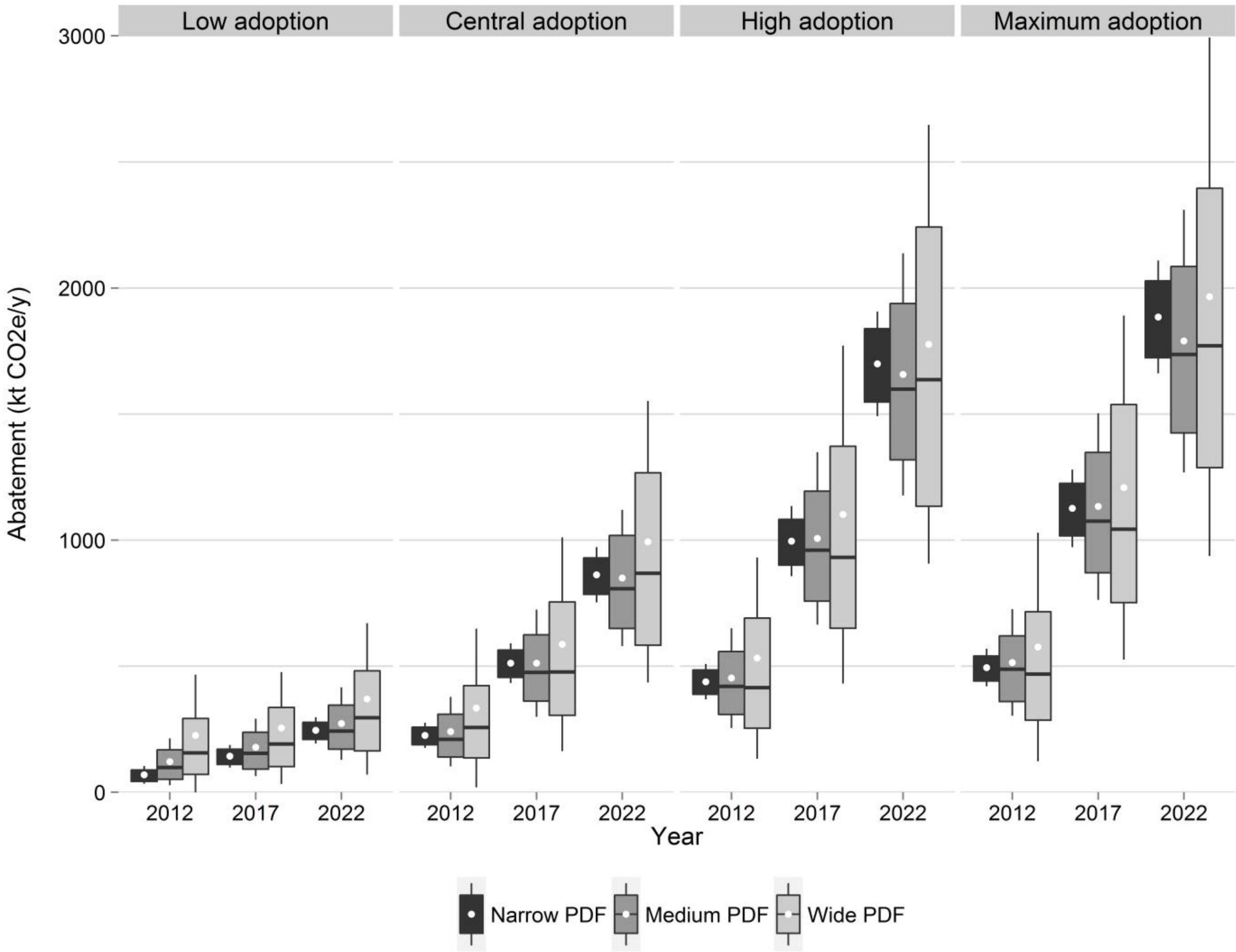

Figure 3 Uncertainty of the cost-effective abatement. Boxes represent lower and upper quartile, black line is the median, light grey dot is the mean, and whiskers represent one standard deviation from the mean in both directions

Uncertainty in the cost-effectiveness and abatement potential of the mitigation options

The uncertainty in the cost-effectiveness of the mitigation options is, on one hand, related to the parameters of the options that eventually define their stand-alone cost-effectiveness, and is also related to the uncertainty in the IFs and the ranking of the options. Figure 4**Error! Reference source not found.** presents the stand-alone and the interaction cost-effectiveness of the mitigation options for three levels of uncertainty (for: all input group uncertainties combined; 2022; central adoption assumption (CFP); truncated normal distribution). The range of the 95% CI of the stand-alone cost effectiveness (CE) for the fifteen options lies between £0 and £227 (t CO_2e)$^{-1}$, £0 and £658 (t CO_2e)$^{-1}$, £0 and £1,847 (t CO_2e)$^{-1}$ for narrow, medium and wide PDFs – very large ranges compared to a shadow price of carbon at £29 (t CO_2e)$^{-1}$.

The uncertainty of the CE corresponded with the mean CE: higher absolute values resulted in larger CI range. The CE of *Using reduced tillage and no-tillage techniques* had the largest CI in all three scenarios and *Separating slurry applications from fertiliser applications by several days* and *Use composts and straw-based manures in preference to slurry* had the lowest 95% CI range. These latter two options' unitary costs were £0 ha^{-1}, resulting in no observable uncertainty in the cost-effectiveness (as the PDF generation methodology calculated the 95% CI as a product of the mode and a constant). The CV show a varied picture among the three PDF assumptions; with the wide PDF *Improving land drainage* is the most uncertain relatively to the mean, while in the other PDF scenarios *Separating slurry applications from fertiliser applications by several days* is the least certain. Relatively the most certain (i.e. lowest CV) option is *Using controlled release fertilisers*.

The uncertainty of the interaction cost-effectiveness was higher than the stand-alone cost-effectiveness since the uncertainty in the IFs adds a further source of uncertainty via changing the ranking of the options and the effects one option have on the abatement potential of other options. Consequently, the least cost-effective options have the highest uncertainty (Figure 4)**Error! Reference source not found.**. The 95% CI of the interaction CE of *Using biological fixation to provide N inputs* was between 33,000 and nearly 3,000,000 £ (t CO_2e)$^{-1}$ in the three PDF assumptions, with three more options having very high CIs (*Reducing nitrogen fertiliser*, *Using controlled release fertilisers*, *Adopting systems less reliant on inputs*); clearly highly influenced by the combination of interaction calculation and uncertainty propagation methodologies. The increase in the range of the 95% CI from stand-alone CE to interaction CE is at least 10-fold for all but the six most cost-effective options in the medium PDF assumption.

As expected, the uncertainty of the cost-effectiveness of the options increases with increasing uncertainty level. Interestingly this, in turn, changes the probability of the mitigation options being cost-effective: with higher uncertainty the median CE values moving closer to the shadow price of carbon (SPC), and the probability of the options switching from being cost-ineffective to cost-effective (and *vice versa*) becomes higher. For example, the median stand-alone CE of *Using nitrification inhibitors* is £53 (t CO_2e)$^{-1}$ with narrow PDF, and its probability of falling under the SPC was 6.6%. With wide PDF the CE is £39 (t CO_2e)$^{-1}$ and the probability of being cost-effective increased to 38.8%.

Regarding the abatement of the mitigation options, the smallest 95% CI ranges belonged to the options with lowest abatement potential and vice versa. Under the medium PDF assumption the lowest CI range was 16 kt CO_2e y^{-1} (*Separating slurry applications from fertiliser applications by several days*, with interactions) and the highest was 778 kt CO_2e y^{-1} (*Improving land drainage*, stand-alone). However, if we compare the uncertainty range with the mean, *Reducing nitrogen fertiliser*, *Using controlled release fertilisers* and *Using nitrification inhibitors* had the lowest uncertainty (i.e. the lowest CV) in stand-alone calculations and *Improving land drainage*, *Improving the timing of mineral nitrogen application* and *Adopting systems less reliant on inputs* has the lowest CV with interactions.

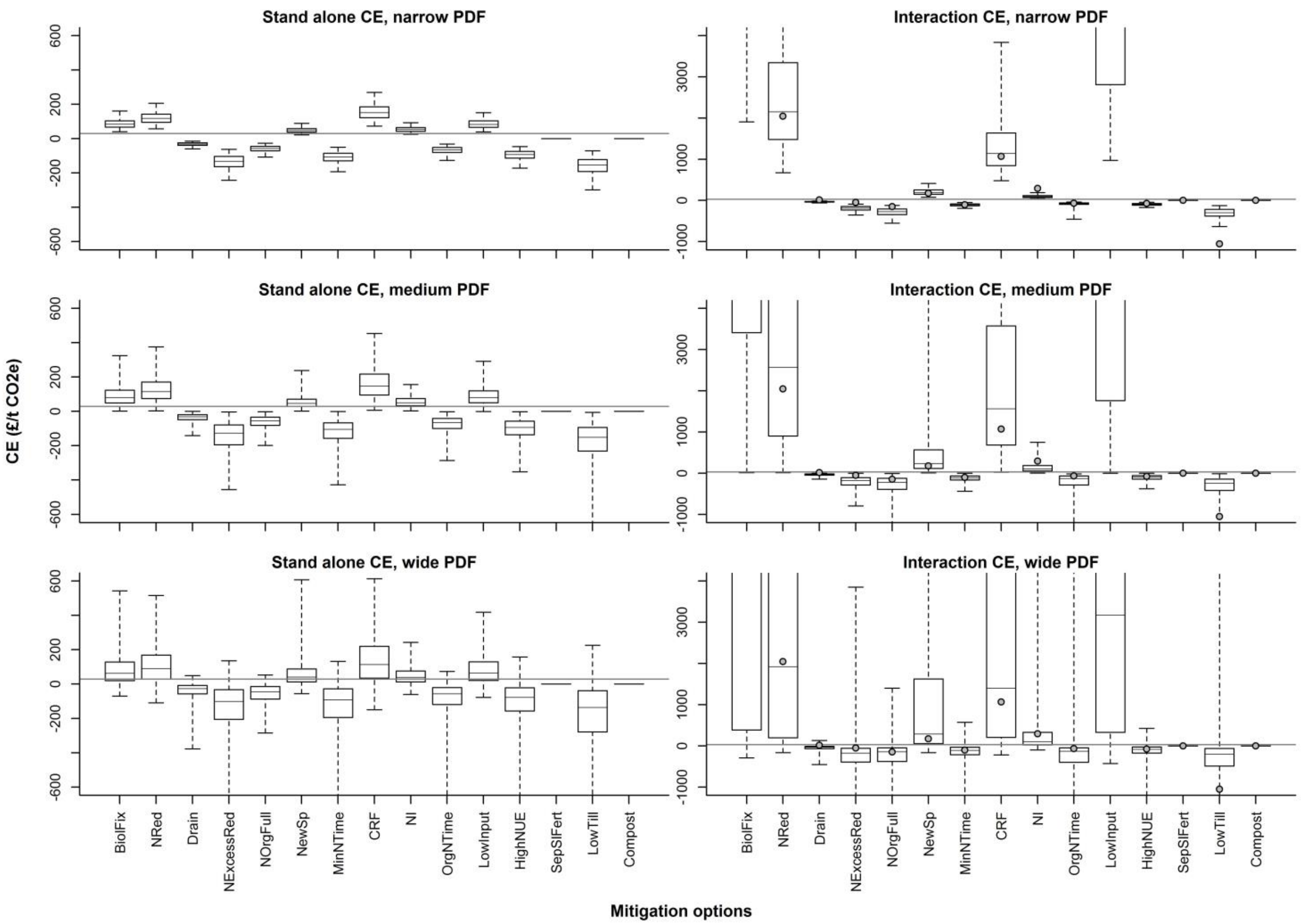

Figure 4 Stand alone and interaction CE of the mitigation options (2022, CFP, all sources combined, truncated normal distribution). Whiskers are 95% CI. The grey line represents the SPC, dots represent corresponding Scottish interaction CE values from (Moran et al., 2008)

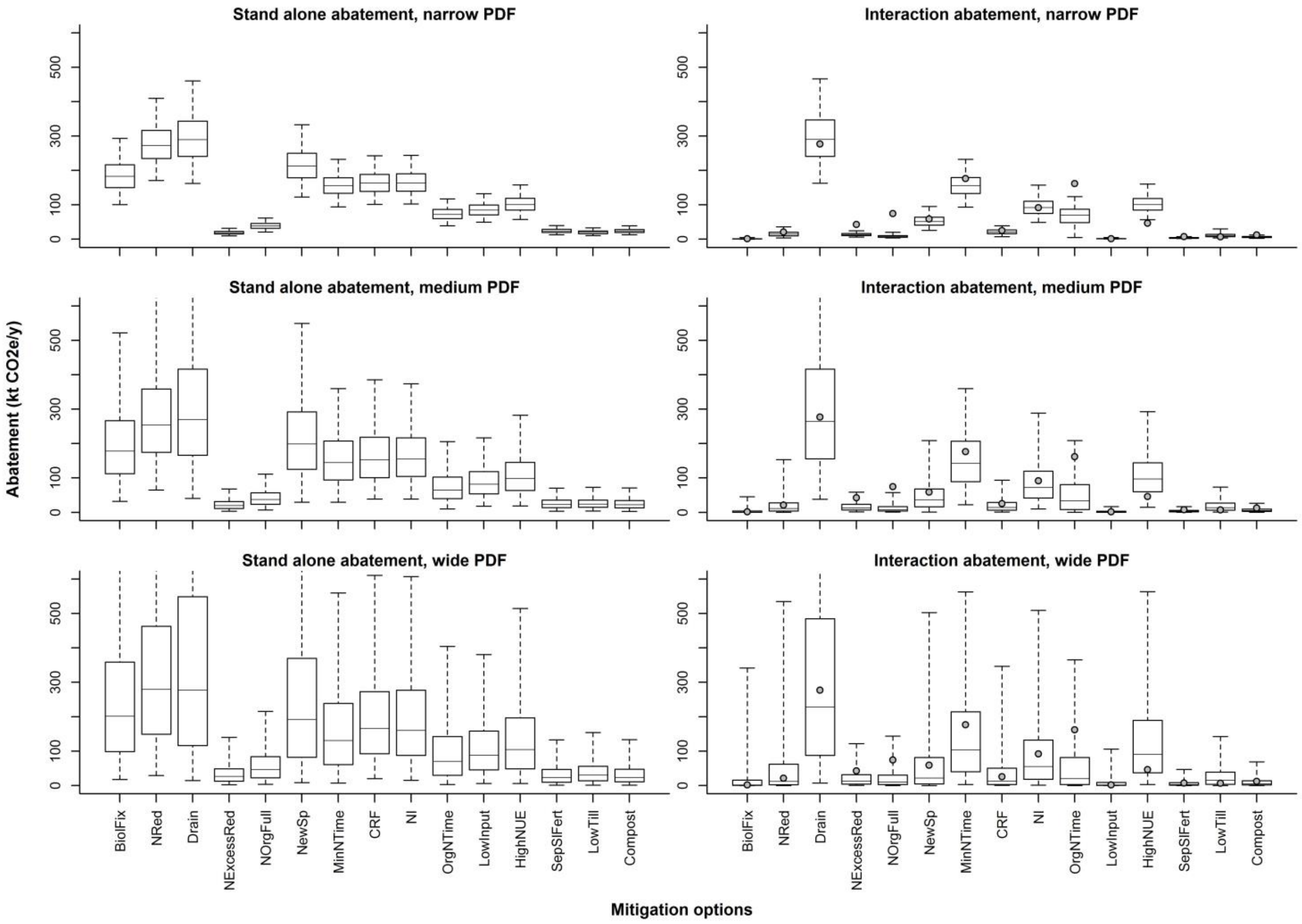

Figure 5 Stand alone and interaction abatement potential of the mitigation options (2022, CFP, all sources combined, truncated normal distribution). Whiskers are 95% CI, dots represent corresponding Scottish interaction abatement values from (Moran et al., 2008)

Our analysis has boundaries and makes assumptions which need to be highlighted. Most importantly, the uncertainty of cost-effective GHG abatement potential depends on uncertainty about the marginal abatement costs and benefits. The latter aspect has not been quantified in this study. A first approach could utilise the uncertainty range of the carbon price as used by the UK Government (DECC, 2009). Furthermore, more detailed information on the uncertainties, particularly using individual uncertainty assumptions for each variable instead of universal uncertainties for input groups could give more refined results, which is important when considering how the uncertainty of the cost-effectiveness of mitigation options compare. The GHG mitigation options often have positive or negative side, or, better co-effects (e.g. on water and air quality). We have not considered these effects and the associated uncertainties. However, including the information in the assessment can significantly shift the cost-effectiveness of individual mitigation options, and therefore might alter the uncertainty of cost-effective GHG abatement potential (Glenk and Colombo, 2011). Finally, emerging information about the uncertainties of the abatement rate of certain mitigation options could be included in future MACC analysis, along with a more detailed representation of net cost uncertainties.

5. Conclusion

This analysis sheds light on the uncertainty associated with estimated cost-effective GHG abatement in an agricultural MACC. Propagating the statistical uncertainty through the MACC addresses important policy questions: i) what are the uncertainties in future mitigation effort, ii) how can uncertainties be reflected in policy development, and iii) how much resource should be allocated to reducing these uncertainties?

What are the uncertainties?

Agricultural MACCs embed complex uncertainties, relating to the wide range of information sources used to build them. While part of these uncertainties can be quantitatively assessed, there are "unknown unknowns"; these deep uncertainties need acknowledgment and consideration, particularly for longer-term mitigation pathways. The quantifiable uncertainty of the cost-effective abatement potential from Scottish agricultural land suggests that the probability of the actual abatement being less than half of the estimated abatement level is between <1% (in the scenario with lowest uncertainty) and 32% (in the scenario with highest uncertainty). The majority of the mitigation options were cost-effective with a certain likelihood in the medium and wide uncertainty scenarios, suggesting that the cost-effectiveness threshold could be used as an indicative metric, as options with CE above it might actually be cost-effective.

How to cope with the uncertainties?

The case study revealed potentially high uncertainties in the Scottish agricultural (crop and soil management) MACC in terms of both the mitigation potential and cost-effectiveness of the options. Different policy approaches can be used to address this. In case of very high uncertainties in the cost-effectiveness estimate or the abatement potential, decision makers may choose to exclude options from further consideration for policy support until more robust evidence becomes available (e.g. improving drainage of agricultural land and administering propionate precursors to cattle were excluded from Scottish agricultural mitigation policy proposals due to high uncertainty of the abatement potential and uptake, respectively (Scottish Government, 2011; Scottish Government, 2013)). Regular updating of the MACC with new evidence gradually reduces the uncertainty of future estimates (Eory *et al*., 2015; MacLeod *et al*., 2010; Moran *et al*., 2008), and therefore aids policy development. Flexible support mechanisms can also help tackle part of the uncertainty arising from variability between farms. Farm advisory services and targeted policies can consider the individual circumstances of farm businesses. We can also be more guarded in excessive extrapolation of unadjusted results from national studies.

How much effort to invest in reducing uncertainties?

Reduction in uncertainty could be achieved via improvement in data reporting, including better accessibility of experimental and modelling data and clearer disclosure of uncertainty. The UK GHG emission inventory now includes an assessment of the uncertainty in IPCC coefficients and activity data (Milne *et al*., 2014). As experimental evidence on the technical abatement potential of mitigation options is expanding, meta-analysis is becoming possible for more mitigation options (see for example Akiyama et al., 2010; Qiao et al., 2015; Veneman et al., 2016). Despite this promising trend, reporting of uncertainty and the main drivers of variability tend to be lax and inconsistent (Buckingham *et al.*, 2014); suggesting the development and wide scale adoption of common reporting guidance would be highly beneficial.

Further evidence should be gathered in areas that have high levels of uncertainty and that contribute disproportionately to output uncertainty (Heijungs, 1996). In this study, the uncertainties in adoption and abatement rates are the most important, while uncertainties in the net cost and activity levels were least important contributors to the uncertainty of the cost-effective GHG abatement. Reducing adoption rate uncertainty requires improved statistics on current farm practices and improved understanding of likely future behaviours, while reducing uncertainty of abatement rates depends on targeted biophysical experimental and modelling exercises. The uncertainty associated with the input of subjective expert opinion for some model variables is particularly challenging to evaluate. This area is rarely explored, with some notable exceptions in energy technology assessment (Baker *et al*., 2009a; Baker *et al*., 2009b). Further quantitative evaluation of this source of information is warranted.

References

Akiyama, H., Yan, X., and Yagi, K. 'Evaluation of effectiveness of enhanced-efficiency fertilizers as mitigation options for N_2O and NO emissions from agricultural soils: Meta-analysis', *Global Change Biology*, Vol. 16, (2010) pp. 1837-1846.

Baker, E., Chon, H., and Keisler, J. 'Advanced solar R&D: Combining economic analysis with expert elicitations to inform climate policy', *Energy Economics*, Vol. 31, Supplement 1, (2009a) pp. S37-S49.

Baker, E., Chon, H., and Keisler, J. 'Carbon capture and storage: combining economic analysis with expert elicitations to inform climate policy', *Climatic Change*, Vol. 96, (2009b) pp. 379-408.

Berger, T. and Troost, C. 'Agent-based modelling of climate adaptation and mitigation options in agriculture', *Journal of Agricultural Economics*, Vol. 65, (2014) pp. 323-348.

Buckingham, S., Anthony, S., Bellamy, P.H., Cardenas, L.M., Higgins, S., McGeough, K., and Topp, C.F.E. 'Review and analysis of global agricultural N_2O emissions relevant to the UK', *Science of the Total Environment*, Vol. 487, (2014) pp. 164-172.

DECC 'Carbon valuation in UK policy appraisal: A revised approach', Climate Change Economics, Department of Energy and Climate Change (DECC), (2009) London.

Eory, V., MacLeod, M., Topp, C. F. E., Rees, R. M., Webb, J., McVittie, A., Wall, E., Brothwick, F., Watson, C., Waterhouse, A., Wiltshire, J., Bell, H., Moran, D., and Dewhurst, R. J. 'Review and update of the UK agriculture MACC to assess the abatement potential for the 5th carbon budget period and to 2050', the Committee on Climate Change, (2015).

Eory, V., Pellerin, S., Garcia, G.C., Lehtonen, H., Licite, I., Mattila, H., Lund-Sørensen, T., Muldowney, J., Popluga, D., Strandmark, L., and Schulte, R.P. 'Marginal abatement cost curves for agricultural climate policy: state-of-the art, lessons learnt and future potential', *Journal of Cleaner Production*, (2017).

Gibbons, J.M., Ramsden, S.J., and Blake, A. 'Modelling uncertainty in greenhouse gas emissions from UK agriculture at the farm level', *Agriculture Ecosystems & Environment*, Vol. 112, (2006) pp. 347-355.

Glenk, K. and Colombo, S. 'Designing policies to mitigate the agricultural contribution to climate change: an assessment of soil based carbon sequestration and its ancillary effects', *Climatic Change*, Vol. 105, (2011) pp. 43-66.

Golub, A., Narita, D., and Schmidt, M.G.W. 'Uncertainty in integrated assessment models of climate change: Alternative analytical approaches', *Environmental Modeling & Assessment*, Vol. 19, (2014) pp. 99-109.

Hallegatte, S., Shah, A., Lempert, Robert, Brown, C., and Gill, S. 'Investment Decision Making under Deep Uncertainty — Application to Climate Change', Report no. WPS6193, The World Bank Sustainable Development Network, (2012).

Heijungs, R. 'Identification of key issues for further investigation in improving the reliability of life-cycle assessments', *Journal of Cleaner Production*, Vol. 4, (1996) pp. 159-166.

IPCC 'Climate change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change', Cambridge University Press, (2013) Cambridge, United Kingdom and New York, NY, USA.

IPCC 'Climate change 2014: Mitigation of climate change. Working Group III contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change', Cambridge University Press, (2014) Cambridge, United Kingdom and New York, NY, USA.

Kann, A. and Weyant, J. 'Approaches for performing uncertainty analysis in large-scale energy/economic policy models', *Environmental Modeling & Assessment*, Vol. 5, (2000) pp. 29-46.

Kesicki, F. and Ekins, P. 'Marginal abatement cost curves: a call for caution', *Climate Policy*, Vol. 12, (2012) pp. 219-236.

Kesicki, F. and Strachan, N. 'Marginal abatement cost (MAC) curves: confronting theory and practice', *Environmental Science & Policy*, Vol. 14, (2011) pp. 1195-1204.

Knaggard, A. 'What do policy-makers do with scientific uncertainty? The incremental character of Swedish climate change policy-making', *Policy Studies*, (2013) pp. 1-18.

Kunreuther, H., Gupta, S., Bosetti, V., Cooke, R., Dutt, V., Ha-Duong, M., Held, H., Llanes-Regueiro, J., Patt, A., Shittu, E., and Weber, E. 'Integrated risk and uncertainty assessment of climate change response policies', in: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Minx, J.C., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, S., Kriemann, B., Savolainen, J., Schlomer, S., von Stechow, C., and Zwickel, T. (Eds.), Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. (2014) Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Lempert, R. and Schlesinger, M. 'Robust Strategies for Abating Climate Change', *Climatic Change*, Vol. 45, (2000) pp. 387-401.

MacLeod, M., Moran, D., McVittie, A., Rees, R., Jones, G., Harris, D., Antony, S., Wall, E., Eory, V., Barnes, A., Topp, Cairistiona F. E., Ball, Bruce, Hoad, Steve, and Eory, L. 'Review and update of UK marginal abatement cost curves for agriculture', Committee on Climate Change, (2010).

Meyer-Aurich, A., Schattauer, A., Hellebrand, H.J., Klauss, H., Plochl, M., and Berg, W. 'Impact of uncertainties on greenhouse gas mitigation potential of biogas production from agricultural resources', *Renewable Energy*, Vol. 37, (2012) pp. 277-284.

Milne, A.E., Glendining, M.J., Bellamy, P., Misselbrook, T., Gilhespy, S., Rivas Casado, M., Hulin, A., van Oijen, M., and Whitmore, A.P. 'Analysis of uncertainties in the estimates of nitrous oxide and methane emissions in the UK's greenhouse gas inventory for agriculture', *Atmospheric Environment*, Vol. 82, (2014) pp. 94-105.

Milne, A.E., Glendining, M.J., Lark, R.M., Perryman, S.A.M., Gordon, T., and Whitmore, A.P. 'Communicating the uncertainty in estimated greenhouse gas emissions from agriculture', *Journal of Environmental Management*, Vol. 160, (2015) pp. 139-153.

Moran, D., MacLeod, M., Wall, E., Eory, V., McVittie, A., Barnes, A., Rees, R.M., Topp, C.F.E., Pajot, G., Matthews, R., Smith, P., and Moxey, A. 'Developing carbon budgets for UK agriculture, land-use, land-use change and forestry out to 2022', *Climatic Change*, Vol. 105, (2011) pp. 529-553.

Moran, D., MacLeod, M., Wall, E., Eory, V., Pajot, G., Matthews, R., McVittie, A., Barnes, A., Rees, R., Moxey, A., Williams, A., and Smith, P. 'UK marginal abatement cost curves for the agriculture and land use, land-use change and forestry sectors out to 2022, with qualitative analysis of options to 2050', Report no. RMP4950, Committee on Climate Change, (2008).

Myhre, G., Shindell, D., Breon, F.-M., Collins, W., Fuglestvedt, J., Huang, J., Koch, D., Lamarque, J.F., Lee, D., Mendoza, B., Nakajima, T., Robock, A., Stephens, G., Takemura, T., and Zhang, H. 'Anthropogenic and natural radiative forcing', in: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P.M. (Eds.), Climate Change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. (2013) Cambridge Univeristy Press, Cambridge, United Kingdom and New York, NY, USA, pp. 659-740.

Olander, L., Wollenberg, E., Tubiello, F., and Herold, M. 'Advancing agricultural greenhouse gas quantification', *Environmental Research Letters*, Vol. 8, (2013) pp. 011002.

Peterson, S. 'Uncertainty and economic analysis of climate change: A survey of approaches and findings', *Environmental Modeling & Assessment*, Vol. 11, (2006) pp. 1-17.

Pierer, M., Amon, B., and Winiwarter, W. 'Adapting feeding methods for less nitrogen pollution from pig and dairy cattle farming: abatement costs and uncertainties', *Nutrient Cycling in Agroecosystems*, Vol. 104, (2016) pp. 201-220.

Price, R., Thornton, S., and Nelson, S. 'The Social Cost Of Carbon And The Shadow Price Of Carbon: What They Are, And How To Use Them In Economic Appraisal In The UK', Department for Environment, Food and Rural Affairs; Crown copyright, (2007) London.

Qiao, C., Liu, L., Hu, S., Compton, J.E., Greaver, T.L., and Li, Q. 'How inhibiting nitrification affects nitrogen cycle and reduces environmental impacts of anthropogenic nitrogen input', *Global Change Biology*, Vol. 21, (2015) pp. 1249-1257.

Salisbury, E., Thistlethwait, G., Young, K., Cardenas, L., and Thomson, A. 'Greenhouse Gas Inventories for England, Scotland, Wales and Northern Ireland: 1990 - 2013', Report no. ED59802/2012/CD8542/GT, Aether, Ricardo-AEA, (2015).

Scottish Government 'Low Carbon Scotland: Meeting the Emissions Reduction Targets 2010-2022 Technical Appendix - The Report on Proposals and Policies', Scottish Government, (2011) Edinburgh.

Scottish Government 'Low Carbon Scotland: Meeting the emissions reduction targets 2013-2027 - The Second Report on Proposals and Policies', Scottish Government, (2013) Edinburgh.

Smith, L.A. and Stern, N. 'Uncertainty in science and its role in climate policy', *Philosophical Transactions of the Royal Society A-Mathematical Physical and Engineering Sciences*, Vol. 369, (2011) pp. 4818-4841.

Veneman, J.B., Saetnan, E.R., Clare, A.J., and Newbold, C.J. 'MitiGate; an online meta-analysis database for quantification of mitigation strategies for enteric methane emissions', *Science of the Total Environment*, Vol. 572, (2016) pp. 1166-1174.

Zehetmeier, M., Hoffmann, H., Sauer, J., Hofmann, G., Dorfner, G., and O'Brien, D. 'A dominance analysis of greenhouse gas emissions, beef output and land use of German dairy farms', *Agricultural Systems*, Vol. 129, (2014) pp. 55-67.